Labor Market Dynamics after Cost-of-Living Shocks*

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Abstract

This paper presents empirical evidence on the importance of labor market adjustments as a buffer against cost-of-living shocks, following relative price changes for goods with inelastic demand. Using the case of energy price changes, I combine 20 years of German employer-employee data with a representative household expenditure survey and rely on regional differences in energy expenditure patterns to identify the pass-through of energy cost shocks into earnings. Changes in nominal earnings offset around 36% of county-specific costs within the same year and fully compensate workers over a five-year window. Selected job-to-job mobility is an important mechanism. Higher exposure to energy price changes both incentivizes workers to change jobs and, conditional on switching, makes transitions more profitable in terms of earnings gains. The empirical results suggest that endogenous labor supply responses are a significant factor in understanding the welfare consequences of price changes more broadly.

Keywords: labor supply dynamics, heterogeneous inflation rates, price-wage pass-through, energy price shocks

JEL classification numbers: J3, J62, E31

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1 Introduction

The surge in inflation fueled by the COVID-19 pandemic and the war in Ukraine led to a rekindled interest in the distributional consequences of relative price changes. Particularly, the stark increases in food and energy prices captured headline news, as both goods feature a low elasticity of demand, resulting in a cost-of-living crisis for individuals for whom they constitute a larger share of total expenditures.[1] Generally, an individual's expenditure composition serves as a valuable first-order approximation to their expected losses in real consumption when prices increase. However, there are several conceivable response margins for individuals trying to alleviate adverse consequences.

In this paper, I study the role of labor market responses as one potential mitigating mechanism after cost-of-living shocks. Workers with a larger idiosyncratic exposure to price changes have an increased incentive to renegotiate wages or change their employers. While recent macroeconomic work suggests that such labor supply responses are an important feature of how workers maintain real wages after increases in the general price level (Afrouzi et al., 2024; Bostanci, Koru and Villalvazo, 2022; Pilossoph and Ryngaert, 2023), we have little empirical evidence from microdata to guide the calibration of labor supply elasticities and earnings responses. In particular, we lack causal evidence on the link between individuals' exposure to price changes and corresponding labor market outcomes. The main contribution of this paper is to make progress in that direction by quantifying the relevance of labor market adjustments to relative price changes for heterogeneous consumers.

To do so, I focus on the case of energy price changes, which are a key driver of inflation inequality between consumers (Corsello and Riggi, 2023), and exploit spatial differences in energy consumption patterns across German administrative counties. Using a representative household consumption survey, I first document a significant amount of location-specific variation in energy expenditures. Conditional on socio-demographics, expenditure shares range from around 6% in some counties to around 13% in others. Local energy expenditures are highly correlated with the available commuting infrastructure and the frequency of adjustments to the housing stock. I combine the local energy expenditure shares with global price trends to construct an energy-specific Laspeyres CPI index. In the second step, I then use 20 years of linked employer-employee registry data to map the local energy price indices into labor market outcomes of employees residing in the

[1] In line with this, a series of recent studies highlight the role of consumption heterogeneity in shaping welfare implications of energy price increases (Känzig, 2023; Kuhn, Kehrig and Ziebarth, 2021; Oni, 2023; Pieroni, 2023; Bobasu, Dobrew and Repele, 2024) and other inflationary episodes (Cardoso et al., 2022; Del Canto et al., 2023; Pallotti et al., 2024).

respective counties.

Estimating the pass-through of energy prices into nominal earnings indicates considerable flexibility relative to local inflation rates. In the short term, i.e., considering year-to-year changes, differences in earnings adjustments cover between 36 and 43% of the additional costs arising from county-specific energy price exposure. This still implies a divergence in real consumption between high and low-exposure areas, but the effect is reduced relative to a benchmark in which earnings adjust according to average inflation rates. While pass-through is not one-to-one in the short-term, it is natural to assume that not all labor market adjustments take place on a short-term basis – e.g., because of mobility frictions or a lower frequency of wage adjustments. In fact, considering longer time horizons reveals an increasing pass-through over time such that over five years, earnings changes fully recover county-specific increases in costs for the average employee.

Constructing the CPI index as a combination of location-specific exposure shares and global price changes renders the main variable of interest similar in its structure to that of shift-share instruments. This greatly facilitates the exposition of the necessary assumptions to identify the differential pass-through of price changes into nominal earnings. To identify a causal effect, one either has to rule out other shocks that correlate with energy prices or the existence of other unobserved local conditions that mediate the impact of energy price changes and correlated shocks. I demonstrate that the results are unaffected when instrumenting energy price changes with carbon price policy surprises obtained from Känzig (2023) and when allowing yearly fixed effects to vary over several local labor market indicators. While one threat to identification is that energy price changes might affect labor demand in a way that is correlated with local consumer expenditures on energy, I argue that this concern is unlikely to be quantitatively important. All empirical specifications compare only individuals working for firms of similar size and within the same narrowly defined 3-digit sector. This allows me to contrast two individuals who differ in their consumption profiles but work for firms that face comparable cost shocks in terms of energy inputs into production.

The empirical results show that selected job-to-job mobility plays an important role in determining the pass-through of energy prices into earnings. On the one hand, employees in more exposed counties are more likely to switch employers in response to changes in energy prices – a one standard deviation higher energy cost shock is associated with a 0.5 percentage points higher rate of yearly job mobility. On the other hand, conditional on switching, job switches in higher-exposure counties are associated with steeper increases in nominal earnings. I provide evidence that this partially results from targeting firms that offer overall higher levels of earnings. Job switchers in high energy-expenditure counties are also more likely to switch their occupation and sector of work, conditional on transitioning to another firm.

When considering treatment effect heterogeneity, a strong predictor of a high pass-through is age. Workers between 25 and 40 recover increased costs quickly, whereas the correlation between county-specific energy inflation and earnings is essentially zero for workers in the late stages of their careers (ages 56 to 65). Younger workers tend to switch jobs more frequently and their job mobility responds more elastically to increased energy costs. While job mobility is a key route to recovering incurred losses, this is not uniformly so across the population. Men and women, for instance, have comparable estimates for the elasticity of earnings to energy prices, but women react considerably more flexibly in terms of job mobility. Women consequently profit less from job transitions than men.

There are several theoretical frameworks to draw from when trying to model the link between cost-of-living shocks and labor supply responses. In the competitive and frictionless benchmark case, in which workers are paid according to their marginal productivity, earnings should increase if workers respond by working longer hours or if aggregate employment falls and the marginal productivity of labor increases. I find no evidence that workers with a higher flexibility of working hours experience a stronger pass-through of energy prices into earnings, and aggregate employment in high-expenditure counties does not decrease differentially. In fact, higher energy costs for consumers are positively related to aggregate employment. The empirical evidence also suggests that part of the increase in earnings is attributable to switches between firms with different wage levels. The fact that workers are increasingly willing to do these switches when energy costs increase implies that they are not possible at zero cost.

To provide intuition for the empirical analysis, I therefore introduce a simple theoretical framework with local labor markets and firms with (exogenous) heterogeneous amenities in the style of Card et al. (2018). Workers care about both consumption and amenities, which, from their perspective, makes firms imperfect substitutes. This introduces frictions to labor mobility and endows firms with some degree of wage-setting power. Workers consume a general consumption good and an exogenously supplied energy good. In the model, an exogenous increase in energy prices incentivizes workers to reassess the relative importance of firm-specific amenities and wages. This elevated focus on wages increases the elasticity of labor supply firms face, which they internalize in their wage-setting behavior. Since firms cannot observe workers' preferences, they raise wages throughout, reducing their profits but discouraging some workers from leaving. The ones that do leave are positively selected for wage increases.

The model explains why pass-through is non-zero for both job stayers and switchers, albeit higher for the latter group. At the same time, it has the welfare implication that while labor supply responses reduce the distributional burden of price shocks in terms of consumption, this comes at the cost of a differentially large reduction in non-wage amenities. Related observations were recently made by Guerreiro et al. (2024) and Afrouzi et al. (2024) who both argue that workers' responses to inflation, such as bargaining, strikes, or job search, have severe welfare consequences beyond their impact on earnings. The suggested theoretical mechanism applies to price increases of any good with a relatively low elasticity of demand. For them, price increases trigger a stronger income effect, which increases the appeal of labor market responses. While the role of energy prices in overall inflation inequality is considerable (Corsello and Riggi, 2023), and an analysis based on energy is, therefore, of interest by itself, this implies that similar labor supply responses are likely to matter quantitatively also in the case of goods such as housing or food. The results of this paper are thus likely to be of broader relevance than just for the case of increases in energy prices.[2]

Related Literature and Contribution. Reflecting a difference in focus on large macroeconomic general equilibrium models with several dimensions of heterogeneity, previous work studying the distributional implications of price shocks typically models wages as sticky (Bobasu, Dobrew and Repele, 2024; Pieroni, 2023), labor supply as fixed (Kuhn, Kehrig and Ziebarth, 2021), or labor markets as competitive (Oni, 2023). All three assumptions suggest a limited role for labor supply responses to be of quantitative importance for the distributional impact of price shocks. Cardullo and Sechi (2023) consider labor supply responses to changes in the prices of housing in a model in which employed and unemployed workers differ in their expenditures on housing, and wages are determined by Nash bargaining. However, in the absence of microdata, a positive relationship between the exposure to price changes and nominal wages is assumed rather than tested.

Closer to this paper, there is evidence that wages fall less after energy price increases for individuals with less than a high school degree relative to peers with higher education levels (Del Canto et al., 2023). While the overall negative impact on wages likely reflects a drop in labor demand, the differentially weaker effect on less-educated individuals is in line with the results of

[2] The implications when moving beyond necessity goods are less clear-cut. Previous work by Del Canto et al. (2023), for instance, highlights that energy price spikes are mostly regressive, whereas monetary policy shocks are mainly progressive.

this paper since energy expenditure shares decline in education.[3] Studying the recent high inflation episode in the U.S. and currency-devaluation-driven inflation in Argentina, respectively, Afrouzi et al. (2024) and Blanco, Drenik and Zaratiegui (2024) demonstrate a lower decline and a faster recovery of real wages at the bottom end of the income distribution. At the same time, Broer, Kramer and Mitman (2024) and Känzig (2023) provide evidence that after energy prices increase, wages fall more strongly at the bottom of the income distribution than at the top. Combining household consumption data with high-quality registry data from the labor market, in this paper, I make the link between consumption baskets and income adjustments explicit and calculate the share of increased costs accounted for by changes in earnings, relying on rich linked employer-employee data that allows the tracking of individuals over time.

In addition to the literature on the distributional consequences of price shocks for consumers with heterogeneous consumption bundles, this paper also speaks to the long-standing debate on price-wage spirals. While the majority of work in this area studies the path from wage growth to inflation, a few recent papers focus on the less-studied reverse path and highlight the impact of realized (Bostanci, Koru and Villalvazo, 2022) and expected (Pilossoph and Ryngaert, 2023) inflation on wages. They first show empirically that search effort increases in response to price shocks and then use this fact to inform search models, which predict a partial escape of real wage losses for employees by switching to other employers. Bloesch, Lee and Weber (2024) argue that in general equilibrium, the role of on-the-job search for explaining the pass-through of prices into wages might be quantitatively limited because an increase in overall search effort also increases the probability that firms find a replacement for any given worker.[4] Afrouzi et al. (2024) calibrate a large frictional labor market model with costly renegotiations and search efforts to highlight that even if workers are able to recover real wage losses after price increases through job transitions, this comes at a utility cost that decreases welfare overall.

I complement and contribute to this work in two important dimensions. First and foremost, the results of this paper cover empirical ground by exploiting large-scale linked employer-employee data instead of surveys and aggregate data. In combination with a quasi-experimental framework,

[3] Kehrig and Ziebarth (2017) study a complementary case to this paper, in which consumers are identical in their consumption bundles, but firms differ in the energy intensity of their production. In response to an energy price shock, this differentially affects labor demand which has repercussions for the inequality of earnings across worker skill types and space. Chan, Diz and Kanngiesser (2024) focus on optimal monetary policy when energy and labor are complementary inputs into production.

[4] This is not the case in the theoretical framework I consider, where firms' labor market power is derived from workers' preferences for firm-specific amenities and not from search frictions, and indeed, I do find a considerable pass-through of cost increases into nominal earnings.

this allows me to identify the causal impact of price shocks on the distribution of real wages for a representative set of workers. I provide estimates of income and job mobility elasticities to guide future work. Second, the conceptual focus of this paper is on idiosyncratic rather than average inflation rates. In contrast to previous work that seeks to model the dynamics through which nominal earnings keep up with the general price level, my focus is on the distributional impact of relative price changes. Even if consumers keep real earnings constant relative to average inflation rates, consumption heterogeneity combined with relative price changes can imply maintained real earnings losses for consumers who spend a larger share on hard-to-substitute goods (necessities). In fact, Dustmann, Fitzenberger and Zimmermann (2022) highlight that not accounting for differential trends in housing expenditures leads to an underestimate of the increase in income inequality in Germany between the 1990s and 2013.

On a theoretical level, the paper draws heavily from the extensive literature on wage-setting firms and monopsony power (Manning, 2021), and in particular from Card et al. (2018), Berger, Herkenhoff and Mongey (2022), and Lamadon, Mogstad and Setzler (2022) who rely on preference heterogeneity for amenities to derive insights on firms' market power and worker-firm rent-sharing. The main contribution of the paper is empirical. I speak to the theoretical work by embedding a consumption problem with non-homothetic preferences into a discrete firm choice problem. This allows me to link exogenous price movements to the marginal utility of income, which endogenously determines the minimum wage firms need to post in order to attract any workers.[5] In recent work, Kline (2025) highlights the central role of the distribution of workers' outside options for determining firms' labor market power.

Road Map. The remainder of this paper is organized as follows: Section 2 introduces the institutional setting in which wages in Germany are set, as well as the data sources underlying the empirical analysis. Sections 3 and 4 present the empirical framework and results, respectively. Section 5 introduces a theoretical framework rationalizing the link between idiosyncratic inflation rates and changes in labor supply decisions. Section 6 finally offers some concluding remarks.

[5] In a similar vein, recent work by Mongey and Waugh (2023) provides an in-depth discussion of how exogenous shifts in the marginal utility of income affect the pricing decisions and mark-ups of firms.

2 Background and Data

Before turning to the empirical analysis, this chapter briefly outlines some key features of the German context in which the study is situated. It then describes the underlying data sources and discusses the measurement of key concepts. The link between heterogeneous consumption patterns, price trends, and labor market outcomes, which is necessary for the empirical exercise, naturally imposes a heavy burden in terms of data requirements. Since no comprehensive data set containing all the relevant information exists for Germany, I make use of and combine several data sources.

Background: Spatial Heterogeneity and Wage Setting in Germany

The empirical exercise relies on spatial heterogeneity to construct differences in the exposure to energy price shocks. In particular, differences in the share of total expenditures dedicated towards energy across German counties. Today, Germany is divided into 16 regions that aggregate a total of 400 administrative counties. Counties include 106 independent cities and 294 further counties, varying vastly in size, population, and geography. The delineation of counties changed slightly over time: some counties were separated to form newer and smaller counties, and others were unified. All data sets used in this study rely on a time-consistent geographic definition that includes 400 counties, which serve as local labor market proxies.

The goal is to relate the heterogeneity in the intensity of price shocks across counties to changes in labor market outcomes. Since traditionally, wages in Germany were determined by collective bargaining agreements at the more aggregate sector-by-region level, such a link is not necessarily obvious at first. As excellently described in great detail by Dustmann et al. (2014) and Jäger, Noy and Schoefer (2022), however, the German institutional arrangements for wage determination have seen a drastic transition from a system mainly characterized by collective bargaining agreements to one in which firm-level negotiations play an increasingly important role. Firm-specific work councils are a central player in this paradigm of co-determination. Negotiations between them and individual employers offer a higher level of flexibility relative to local conditions, increasing the likelihood of upward but also downward deviations from collectively bargained wages. Jung and Schnabel (2011) show that the payment of wage cushions on top of collectively bargained wage floors is common in Germany, whereas Boeri et al. (2021) illustrate that the downward flexibility of wages allows for a higher correlation between local productivity levels and wages in Germany than in Italy, which leads to lower geographical differences in unemployment.[6]

[6]As highlighted by Card and Cardoso (2022), the payment of wage cushions on top of wage floors that resulted

More recently, Caldwell, Haegele and Heining (2024) provide evidence from firm and worker surveys that individual-level bargaining is an increasingly relevant feature of the German labor market. The degree to which this flexibility allows workers to be compensated for local increases in the cost of living is the empirical question this study seeks to answer.

Labor Market Data: BHP and SIEED by IAB-FDZ

For labor market outcomes, I use two data sets provided by the research data center of the federal employment agency at the Institute for Employment Research (IAB-FDZ): the Establishment History Panel (BHP) and the Sample of Integrated Employer-Employee Data (SIEED). The BHP is based on yearly 50% random samples of German establishments in the social security registry, i.e., of all establishments with at least one employee liable to social security.[7,8] It contains information on the number of employees by skill group, gender, part-time/full-time status, and age, as well as information on average compensation for full-time employees and some moments of the within-establishment distribution (percentiles 25, 50, and 75). It also provides time-consistent sector classifications at the 3-digit level and the administrative county in which the firm operates. Importantly, the BHP, while being sourced from yearly cross-sections, is still set up as a panel that links firms across years (up to a maximum period of 1975 - 2021) and consequently allows analyzing time trends in wages for a representative sample of German firms. In line with the availability of the employer-employee and consumption data described below, I restrict the sample to the time period 1998 to 2018. A further restriction excludes firms that predominantly employ marginal part-time employees (for whom no income data is available).[9] The resulting sample consists of 17,584,804 firm$\times$year observations, with 1,892,605 unique firms.

Similarly to the BHP, the basis for the SIEED data set is a 1.5% random sample of firms in the Social Security registry. However, the unit of observation is an individual employee. The SIEED links each included firm to their employees in a respective year. For all included employees, the

from collective bargaining agreements is, of course, a common occurrence in Europe that is not necessarily linked to the presence of worker councils alone.

[7] As of 1999, establishments with at least one marginal part-time employee are also included, irrespective of whether they also employ workers with contracts subject to social security.

[8] In the data, establishments are defined as "regionally and economically delimited units" (Ganzer et al., 2022), which is not equivalent to a production plant, since it aggregates plants within an administrative district/county. Although technically a firm is in some cases a further aggregation of different establishments, the remaining text will refer to each observation in the BHP and SIEED data as firms and establishments interchangeably.

[9] To exclude firms with predominantly marginal part-time employees, I first drop all firms that only employ marginal part-time employees. In the next step, I drop all firms with average daily wages below 13€, which is slightly below the daily amount one would obtain when working in a marginal part-time contract, which was traditionally capped at 400€/month.

SIEED further reconstructs their full employment histories from social security records. This also includes periods of work at firms that are not part of the 1.5% random sample. For them, firm-level information is linked from the BHP. The SIEED data is organized in employment spells, detailing the exact starting day and month of each employment episode. I construct an individual-level yearly panel by classifying the employment spell an individual was in on December 31st of each year as the relevant job. In case, an individual was not employed on December 31st but has been employed at another point in the respective year, I instead rely on this information. If an individual has multiple employments at the same time, I use the length of employment and the daily income as tiebreakers and keep only information of the longer and higher paid spell.

For each included employee, the SIEED allows the tracking of daily earnings and job-to-job transitions over time. Earnings are recorded as gross compensation over the full employment spell, divided by the number of days. Given that the data source is the Social Security Registry, earnings are top-coded to the maximum contribution limit. This concerns 8.4% of all individual-year observations and I impute top-coded wages following the procedure in Dauth and Eppelsheimer (2020) to improve precision when exploring pass-through heterogeneity at the upper end of the income distribution. The SIEED additionally contains information on both the county of work and the county of residence of each employee, as well as their gender, nationality, and educational background. I restrict the sample to individuals in social security employment who are residing in Germany ($\approx$ 0.4% commutes from abroad) and are between 25 and 65 years old. The SIEED data contains information on an individual's county of residence from 1999 onward and covers the time until 2018. In total, the SIEED analysis sample for this study consists of 9,890,162 individual-year observations, with 869,453 unique employees and 655,826 unique associated employers. Table 1 contains summary statistics for the socio-demographic makeup of the sample.[10]

County-Level Consumption Patterns: EVS Data by DESTATIS

To measure heterogeneity in consumption patterns, I rely on the *Income- and Expenditure Survey (EVS, short for Einkommens- und Verbrauchstudie)*, which is administered every 5-years by the Federal Statistical Office of Germany (DESTATIS). The EVS is a repeated cross-section that targets a representative sample of (depending on the survey wave) 42,000 and 55,000 households who are asked to keep detailed records of their income and expenditures for three months. Households are distributed equally across each quarter of the year. I use the EVS waves of 1998, 2003, 2008,

[10]For summary statistics of the BHP data, see Table A1.

Table 1: Summary Statistics – SIEED Data

	Mean	*S.D.*		*Mean*	*S.D.*
Daily Gross Income	98.289	63.25	Sector		
Age	43.528	9.80	*Agriculture & Fishing*	0.009	
Female	0.401		*Mining & Quarrying*	0.007	
German Citizen	0.931		*Manufacturing*	0.243	
Residence: Eastern Germany	0.185		*Utilities*	0.009	
Works Full-Time	0.818		*Construction*	0.060	
Education			*Wholesale & Retail*	0.151	
Below Abitur	0.708		*Hotels & Restaurants*	0.025	
Abitur	0.119		*Transportation*	0.073	
Academic Degree	0.174		*Financial Intermediation*	0.028	
Job Task			*Real Estate & Renting*	0.153	
Unskilled/Semiskilled	0.090		*Education*	0.035	
Skilled	0.664		*Health & Social Work*	0.111	
Complex Task	0.110		*Community & Other Services*	0.042	
Highly Complex Task	0.135		*Public Administration*	0.053	
Changed Job in Past Year	0.164		*Other*	0.001	
Changed Residence in Past Year	0.033				

Notes: The table displays summary statistics for the SIEED data, excluding individuals who are not in social security employment, commute to work from outside of Germany or are not between 25 and 65 years old. Daily gross income is imputed based on the procedure in Dauth and Eppelsheimer (2020). *Abitur* is a dummy variable equal to 1 in case the individual obtained a university-qualifying high school degree. *Below Abitur* consequently indicates individuals with either no high school degree or a high school degree that does not grant access to universities.

2013, and 2018. Expenditures are grouped into the 12 standard categories underlying the computation of consumer price indices: e.g., food and non-alcoholic beverages or shoes and clothing. Importantly, expenditures for electricity, gasoline, gas, oil, and other energy goods are listed as individual items, which allows me to compute expenditure shares for several types of energy usage separately. Besides expenditures and income, the EVS also contains socio-demographic information on household members, such as occupational status, education, nationality, age, and some features of the living environment (apartment/house size in m^2, year in which the house of residence was built, rental vs. ownership status, ...). Finally, each household lists the available stock of durables such as bikes or cars.

Price Trends: Data from DESTATIS

While the EVS data allows me to measure differential exposure to energy price shocks across households, I rely on energy price series that are common across consumers and represent the German average. DESTATIS provides a series of monthly average consumer prices for electricity, heating oil, gas, gasoline, as well as solid fuels, which I use as a price proxy for the residual *other energy* category, which in the EVS data contains coal, wood, other solid fuels, and central heating. I use yearly averages for each price series.

3 Empirical Approach

This section illustrates how the above-described data allows me to identify the pass-through of energy price shocks into earnings. Section 3.1 introduces the empirical framework and discusses the role of the measurement of exposure to energy price shocks in identifying pass-through. Section 3.2 then provides descriptive evidence of exposure heterogeneity and the construction of the corresponding proxy for shocks to the cost of living.

3.1 Framework and Identification

Let $S^g_{i,t-s}$ be the share of energy good $g \in \{Gas, Gasoline, Oil, Electricity, Other\}$ in individual i's total expenditures for the year $t-s$, and let P^g_t be the price of good g at time t. Following the classic Laspeyres approach, we can approximate the contribution of energy to changes in the cost of individual i's idiosyncratic consumption bundles by $C^s_{i,t} = \sum_g S_{i,t-s} \frac{P^g_t}{P^g_{t-s}}$. The goal of the empirical analysis is to relate this cost measure to changes in individual labor market outcomes and, in particular, to changes in income.

As highlighted in the previous section, the employer-employee data set underlying the analysis does not contain information about consumption. I, therefore, proxy $S^g_{i,t-s}$ with good g's expenditure share in individual i's county of residence, c. Consider the following regression, treating the change in individual log earnings from year $t-s$ to year t as an outcome variable:

$$\Delta_s y_{i,c,t} = \alpha_i + \gamma_c + \delta_t + \tau \times C^s_{c,t} + \boldsymbol{X_{i,c,t}\beta} + \epsilon_{i,c,t}, \tag{1}$$

where α_i and δ_t are individual and year fixed effects and $\boldsymbol{X_{i,c,t}}$ is a vector of individual$\times$year-specific covariates, discussed in further detail below.

Given the definition of $C^s_{c,t}$ as the combination of price changes and expenditure shares, τ can be interpreted in two ways. First, as the elasticity of nominal earnings with respect to energy prices for a counterfactual county, in which energy constitutes 100% of expenditures. Second, as the share of direct additional costs incurred by energy price increases that are compensated by changes in income. For $\tau = 1$, county-specific energy cost increases are fully compensated; for $\tau = 0$, there is no correlation between additional costs and income changes. In the case of $\tau \in (0, 1)$, county-specific costs are partly recovered, but higher-expenditure counties suffer stronger losses in real consumption than lower-expenditure counties. I will consider different time frames, s, to estimate short- and long-term responses.

Identification. To interpret τ causally as the effect of energy prices on wages through employees' consumption patterns, the energy price exposure measure $C^s_{c,t}$ needs to be (conditionally) uncorrelated with any unobserved variable that also affects wage changes for individual i in year t, i.e.,

$$\epsilon_{i,c,t} \perp\!\!\!\perp \sum_g S^g_{c,t-s} \frac{P^g_t}{P^g_{t-s}} | (\alpha_i, \gamma_c, \delta_t, \boldsymbol{X_{i,c,t}}). \tag{2}$$

The factor structure of $C^s_{c,t}$, i.e., the combination of local shares and global price shifters, renders this identification issue similar to the reasoning of shift-share instruments: the identifying variation for τ comes from the interaction of the two continuous measures and in turn any threat to identification needs to be correlated with this interaction term to be problematic. The recent work on shift-share instruments suggests either the exogeneity of shocks (here, $\frac{P^g_t}{P^g_{t-s}}$, Borusyak, Hull and Jaravel, 2022) or the exogeneity of shares ($S^g_{c,t-s}$, Goldsmith-Pinkham, Sorkin and Swift, 2020) as two main routes to identification.

A reason motivating the use of movements in energy prices as shocks to the costs of living and not prices for other goods is that energy prices are strongly influenced by trends on the global market and are thus plausibly determined at a higher level of aggregation than that of German counties. One could consequently view $\frac{P^g_t}{P^g_{t-s}}$ as quasi-random from the point of view of a county. However, the absence of a causal relationship running from local economic conditions to global prices does not necessarily imply that both are uncorrelated. Without an explicit instrument for price changes, it is plausible that there exists a shock that is correlated with price trends and differentially impacts counties based on their energy expenditure shares. For example, since energy is mostly characterized as a necessity, its share in total expenditures is decreasing in income, making it more likely that higher energy expenditure counties are also poorer counties on average. If there exists any aggregate shock $Z_t \not\perp \frac{P_t^g}{P_{t-s}^g}$ that differentially affects richer and poorer households, this would be an issue for the identification of τ.[11]

To strengthen the identification strategy, it is therefore helpful to also view the problem from the perspective of share exogeneity. This point of view implies that even if there are unobserved factors driving both price and income changes, τ can still be recovered in the data as long as county-level energy expenditure shares are not correlated with other local conditions that moderate the effect of energy prices. From this perspective, the non-random sorting of households is a clear potential confounder. To address the issue, I rely on adjusted measures of county-specific expenditure shares rather than on simple averages. As detailed in section 3.2 below, I estimate energy expenditure shares for each county, $S_{c,t-s}^g$, adjusting for differences in socio-demographic characteristics of households across space. The residual variation relies on geographic differences between Germany's 400 administrative counties, such as commuting infrastructure or the energy efficiency of housing. The key identifying assumption is that this residual geographic variation is not correlated with household characteristics that moderate the impact of price trends or correlated shocks. I discuss this assumption further in Section 3.2 when introducing the estimation of expenditure shares.

To additionally account for potentially confounding local conditions, $\mathbf{X_{ict}}$ contains a series of county- and individual-level characteristics and their interactions with δ_t. That is, the specification allows yearly shocks to vary over measures of employment concentration, county-level industry composition, unemployment rates, as well as indicators for the 3-digit industry of individual i's firm in period $t-s$, interacted with indicators for terciles of the within-sector firm size distribution. The latter implies that in a given year, I only compare earnings changes in response to energy price shocks for two individuals that, in $t-s$, worked for firms of similar size, operating in the same sector but living in counties with different exposure to the price shocks. This captures common yearly shocks to firms with a similar production process.

[11]One possibility to circumvent this issue is to instrument $\frac{P_t^g}{P_{t-s}^g}$ with policy surprises as in (Känzig, 2023). This approach relies on high-frequency variation in prices, however, which is less appealing in the setting of this paper as wages are typically renegotiated at an annual or lower frequency. Section 4.1 nonetheless includes a specification that uses carbon price changes as an instrument for energy prices. The results from this alternative approach are similar both in magnitude and precision to the main specification.

3.2 Heterogeneous Exposure to Energy Price Shocks: Measurement and Descriptives

As just outlined, identification is partially based on variations in energy consumption patterns that are due to geographic factors and not linked to socio-demographic characteristics such as income or education, which might themselves be important determinants of income changes. Using the EVS expenditure data, I therefore estimate for each survey wave a series of regressions of the type:

$$S^{g}_{h,c} = \pi_c + X_{h,c}\beta + u_c, \tag{3}$$

where $S^{g}_{h,c}$ is the share of expenditures that household h in location c devotes to good $g \in \{Gas, Gasoline, Oil, Electricity, Other\}$, and π_c is a location c fixed effect. $X_{h,c}$ contains socio-demographics of the household, including the total number of household members, the number of employed household members, total expenditures, household gross income, living space per household member in m^2, the number of cars/household member, and the quarter of the year in which the expenditure documentation took place. Additionally, it contains the household head's marital status, occupational status, full-time/part-time status, nationality, educational attainment, gender, and age.

The predictions obtained from (3) when fixing $X_{h,c}$ at its sample mean result in average expenditure shares for location c adjusted for socio-demographic differences between localities.[12] This, for instance, partials out differences in energy expenditure shares that arise mechanically from the fact that energy is a necessity on which households in the upper tail of the expenditure distribution tend to spend a lower share. The remaining variation is based on locality fixed effects, which form the basis of my measure for exposure to energy price shocks.

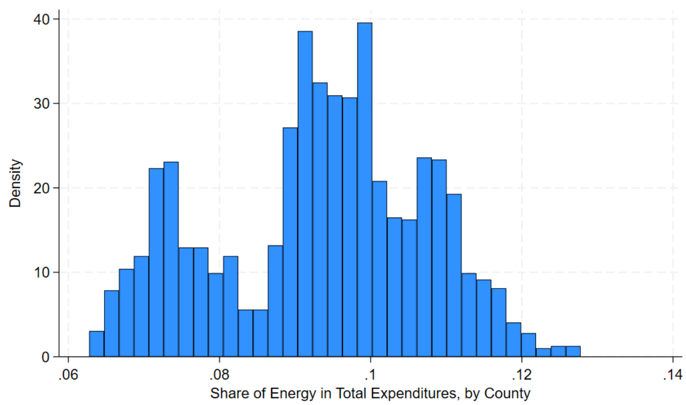
To treat these estimated fixed effects as valid proxies in the spirit of the suggested empirical framework, I need to assume that, conditional on $X_{h,c}$, π_c does not contain information that predicts both the response of income to energy price shocks (e.g., through differences in bargaining power) and a higher energy expenditure share. Importantly, note that $X_{h,c}$ contains household income. This implies that even if unobserved differences between households across space exist and they do get absorbed into π_c, this would only be problematic if they are predictive of income changes in response to energy prices but not of income itself.

[12] One complication in transferring the estimated location fixed-effects to the IAB-FDZ data is that the EVS data contains geographic information at the region by agglomeration-type level and not directly at the level of an administrative county, which is the relevant level of aggregation in the IAB-FDZ data. I harmonize the two geographic measurements by relying on county-level characteristics obtained from the *Federal Institute for Research on Building, Urban Affairs, and Spatial Development (BBSR)*, as detailed in Appendix A.3.

Descriptive Evidence for Heterogeneity in Energy Price Exposure

Predicting county-level expenditures based on specification (3) and EVS data reveals a significant degree of heterogeneity across space, even when keeping the socio-demographic characteristics of households constant. Figure 1 displays the distribution of energy expenditure shares, defined as the sum of expenditure shares over all types of energy g. While energy expenditures are only 6.3% of total expenditures in some counties, they amount to over 12.8% in others. This difference is comparable to the gap in expenditure shares between the highest and lowest income quintiles of households. On average, 9.3% of expenditures are dedicated to energy consumption, and the standard deviation across counties is around 1.2 percentage points.

Figure 1: Estimated Energy Expenditure Shares by County



Note: The Figure shows the distribution of estimated county-level averages for total expenditure shares of energy goods, including gasoline, gas, oil, electricity, and other types of energy. Source: Einkommens- und Verbrauchsstudie 1998, 2003, 2008, 2013 and 2018 each Basic File 3, own calculations. For a year-by-year breakdown, see Figure A2.

Also within finer categories of energy consumption, there is considerable variability across counties. Table 2 breaks energy expenditures down into expenditures on gasoline, gas, oil, electricity, and other types of energy. The largest component is the consumption of gasoline, which on average accounts for 3.9% of total expenditures, whereas oil is the lowest expenditure category, with an average share of 0.7%. However, even in this category, there are some counties in which average households spend 2% of their expenditure budget on oil. Judged by the ratio of standard deviation to mean, oil expenditures are the most variable form of energy consumption across space, followed by the residual category of other energy types, consisting of coal, wood, and other solid fuels, as well as central heating.

By construction, this spatial variation in expenditure shares is not driven by differences in the sorting of households based on average income, age, education, or labor force status.

Table 2: Expenditure Shares for Different Energy Types (in %)

	Mean	*S.D.*	*Min*	*Max*
Gasoline	3.87	0.61	2.23	6.63
Gas	1.31	0.51	0.30	2.75
Oil	0.72	0.39	0.00	1.97
Electricity	2.43	0.39	1.46	3.37
Other Energy	1.00	0.38	0.23	2.08
All Energy	9.32	1.40	6.28	12.78

Notes: The table shows estimated county-level averages for expenditure shares of different types of energy goods. *Other Energy* includes expenditures for coal, wood, and other solid fuels, as well as central heating. Source: Einkommens- und Verbrauchsstudie 1998, 2003, 2008, 2013 and 2018 each Basic File 3, own calculations.

Using information on county-level characteristics provided by the Federal Institute for Research on Building, Urban Affairs, and Spatial Development (BBSR), however, reveals that energy expenditure shares are higher in counties with lower population density, a larger share of commuters, a sparser public transportation network, and a lower frequency of construction of new housing (see Table 3). All these features point in the direction that the variation in energy expenditure shares captures significant spatial heterogeneity in commuting and housing infrastructure.[13]

Table 3: Correlation Coefficients of Expenditure Shares with County Characteristics

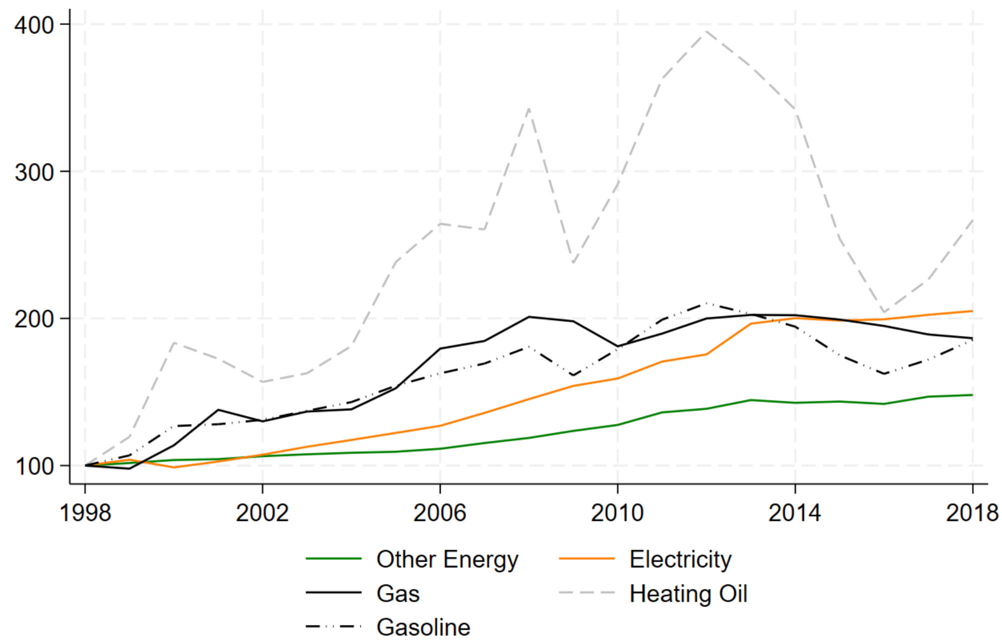
	Population	Population Density	Commuter Share
Energy Exp. Share	-0.217	-0.499	0.090
	(0.000)	(0.000)	(0.011)
	New Housing	**Access to Public Transport**	**Dist. to Regional Center**
Energy Exp. Share	-0.189	-0.469	0.689
	(0.000)	(0.000)	(0.000)

Notes: The Table displays correlation coefficients between county-level expenditure shares in a given year and other county characteristics obtained from the INKAR database at BBSR. P-values are displayed in parentheses. Commuter share is the share of all employees that commute $>$ 50km. Access to Public Transport is the share of inhabitants that live within a 1km radius of a stop for public transport offering at least 20 rides a day. New Housing is the fraction of newly built housing units per 1,000 existing housing units. Distance to Regional Center measures the time in minutes it would require an average inhabitant to reach a regional center (*Oberzentrum*) by car.

While the results above demonstrate the large degree of heterogeneity in exposure to price shocks, Figure A4 displays the magnitude of these shocks by plotting the time series of average German consumer prices for different energy goods over the sample period. Relative to 1998, prices for electricity, gasoline, and gas roughly doubled by 2018, whereas the price of heating oil

[13]For a graphical illustration of the spatial distribution of expenditure shares, see Figure A3.

Figure 2: Consumer Price Series for Energy Goods



Note: The figure plots a series of average yearly prices, normalized to 100 in 1998. Sources: DESTATIS.

increased by a factor of more than three. Prices for the residual category, including solid fuels and wood, saw the most modest increase. Overall CPI inflation for the same period amounts to approximately 32%, highlighting the significant cost increases for energy. Figure A4 further illustrates a non-negligible amount of variation around the overall positive time trend, in particular for gasoline, oil, and gas. This implies that the identification of the cost-wage pass-through will not solely rely on monotonically increasing prices.

One motivation to use energy prices as shocks to the cost of living and not price increases for other goods is that energy prices are plausibly determined at a higher level of aggregation than that of German counties. This facilitates the exclusion of unobserved factors driving both local economic trends and cost increases and implies that a common energy price series is a reasonable approximation for local costs. Unfortunately, there is limited data on county-level prices to corroborate this assumption.[14] The latest available information at this level of granularity stems from the period 2007 to 2009 (the midpoint of the period under study in this paper) and was collected as part of a project by the BBSR (2009). While the BBSR study demonstrates remarkable

[14]Of course, as discussed above, the assumption of common price series across space is not strictly needed as long as the variation in energy expenditure shares is uncorrelated with other local mediators of global shocks.

differences in local price levels (assuming a common consumption basket but using varying prices), it also shows that the variation in prices for gasoline, heating oil, and electricity are minuscule, amounting to cross-county coefficients of variation below 5%. This is less than a quarter of the variation in the price of local public transport, for instance, and one-tenth of the variation in the cost of placing advertisements in local newspapers (see Figure A1 for an overview). I conclude that the assumption of a common energy price series is reasonable.

4 Empirical Results

The empirical results of this paper are presented in three steps. Combining the above-described measure of county-specific cost shocks with employer-employee data, I first demonstrate that nominal earnings respond positively to energy price shocks. In Section 4.2, I then discuss several margins of adjustments underlying this positive earnings response, paying particular attention to job-to-job mobility. Finally, Section 4.3 explores heterogeneity with respect to individual characteristics and asks whether it is possible to identify which subgroups of the population are particularly able to translate cost increases into positive changes in earnings.

4.1 Energy Price Changes and Average Earnings Responses

This section present estimates of specification (1), using county-specific energy-driven cost increases, $C^s_{ct} = \sum_g S^g_{c,t-s} \frac{P^g_t}{P^g_{t-s}}$, as a proxy for individual heterogeneity in shock intensity. The regressions include individual and county fixed effects, such that the model identifies τ from deviations from idiosyncratic time trends in earnings, and additionally adjust for year-by-sector by within-sector-firm-size tercile fixed effects. Standard errors are clustered at the county level.

Table 4 presents estimates for year-to-year ($s = 1$) changes in nominal earnings following changes in the local energy-specific CPIs. The results indicate a non-negligible degree of pass-through. For an average county that dedicates 9.3% of its total expenditures to energy, an increase in the price of energy by 10% implies a cost increase of 0.93%. The results in column (1) suggest that 43% of these additional costs can be recovered within the same year through higher earnings, i.e., earnings increase by 0.4%. Thinking about this in terms of standard deviations, a one standard deviation higher energy cost shock is associated with a 0.6 percentage points higher growth in nominal earnings relative to a mean nominal earnings growth of 3% over the considered sample period. While this still implies a divergence of real earnings between high and low energy-

Table 4: The Effect of Year-to-Year Energy Cost Shocks on Earnings

	$Outcome = ln(Earnings_{it} / Earnings_{i,t-1})$				
	(1)	(2)	(3)	(4)	(5)
Energy Cost Shock	0.427***	0.429***	0.360***	0.385***	0.360***
	(0.057)	(0.053)	(0.050)	(0.070)	(0.045)
N Individuals	869,437	869,395	869,379	869,437	868,794
N Total	9,890,000	9,887,582	9,887,145	9,890,000	9,858,287
Match HHI		✓			✓
Match Energy-Intensity			✓		✓
Match Unemployment				✓	✓

Notes: The Table displays estimates for τ in specification 1, proxying individual energy-price inflation with county-level averages as estimated in Section 3.2: $C^1_{ct} = \sum_g S^g_{c,t-1} \frac{P^g_t}{P^g_{t-1}}$. Each specification includes individual and county fixed effects, as well as year-by-sector by within-sector firm-size tercile fixed effects. Firm size is measured by the number of employees in the firm individual i worked for in year $t-1$. Columns (2) to (4) allow yearly fixed effects to vary over: quintiles of the county-sector-level distribution of employment concentration (Herfindahl-Hirschmann-Index), quintiles of the energy intensity of local production, measured as the share of establishments in each county that are operating in energy-intense sectors (i.e., agriculture, utilities, transportation, manufacturing), and the lagged county-level unemployment rate, respectively. Standard errors are clustered at the county level.

expenditure areas, the gap is narrowed by endogenous labor market adjustments.

Columns (2) through (5) of Table 4 show that the results are comparable across different specifications that allow for common yearly shocks across labor markets with similar characteristics. These include the county-sector-level concentration of employment (Herfindahl-Hirschmann-Index, column 2), the county-level share of establishments that are operating in energy-intense sectors (agriculture, utilities, transportation, manufacturing; column 3), and the lagged county-level employment rate (column 4). Table 5 additionally demonstrates that results are unaffected when yearly energy cost shocks are instrumented with carbon policy surprises taken from Känzig (2023) (column 1) and when the outcome variable consists of changes in top-coded instead of imputed earnings (column 2).

This stability of coefficients lends credibility to the identifying assumption that county-level expenditure shares are uncorrelated with other local mediators of global shocks. Columns (3) and (4) further support this by including a test that is similar in spirit to tests for common trends in difference-in-difference settings. The regressions include leads of the local energy-specific CPI and show that future movements in energy prices do not differentially impact counties with varying energy consumption profiles, providing evidence against trend differences across counties.

Table 5: Year-to-Year Energy Cost Shocks and Earnings: Alternative Models

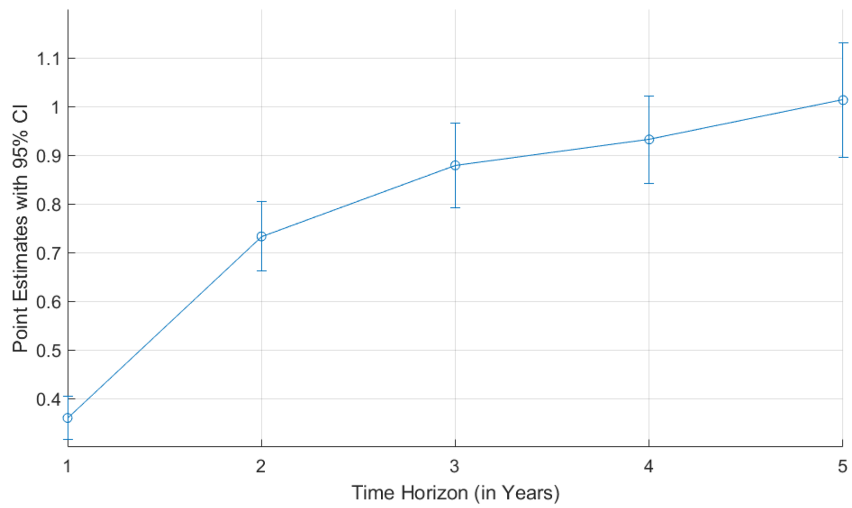
	$Outcome = ln(Earnings_{it}/Earnings_{i,t-1})$			
	(1)	(2)	(3)	(4)
Energy Cost Shock	0.536***	0.428***	0.417***	0.423***
	(0.064)	(0.060)	(0.062)	(0.065)
Energy Cost Shock^{Lead1}			-0.013	-0.068
			(0.054)	(0.070)
Energy Cost Shock^{Lead2}				0.065
				(0.053)
	Carbon IV	Top-Coded Earnings		
N Individuals	869,437	869,752	792,197	733,713
N Total	9,890,000	9,923,313	8,875,534	7,973,022

Notes: The Table presents alternative models of the relationship between energy cost shocks and earnings. Column (1) instruments the energy cost shock from Table 4 with changes in the European carbon prices taken from Känzig (2023) and presents 2SLS results. The instrument is $\left[\sum_g S^g_{c,t-1}\right] \times CPSurprise_t$, where $CPSurprise_t$ is the yearly sum of monthly carbon price changes relative to consumer prices for electricity. Column (2) re-estimates τ in specification 1, using non-imputed/top-coded earnings as the outcome variable. Columns (3) and (4) include leads of the energy cost shock but are otherwise identical to column (4) of Table 4. All specifications include individual and county fixed effects, as well as year-by-sector by within-sector firm-size tercile fixed effects.Standard errors are clustered at the county level.

The Role of Labor Demand. The main identifying assumption of the empirical analysis posits that, conditional on all included covariates, local energy expenditure shares are not correlated with other mediators of energy price shocks. One such potential mediator that would confound the estimation is responses in local labor demand to energy price shocks. If higher energy prices have a differentially negative impact on the labor demand of energy-intense firms and more energy-intense firms are located where consumers spend larger shares of their budget on energy, then the previously documented pass-through would be a lower bound. The opposite would hold if consumers' energy expenditure shares and firms' energy intensity were negatively correlated. To address this issue, columns (3) and (5) of Table 4 adjust for yearly shocks to counties with a similar industry composition. All specifications additionally compare only individuals who, in the previous year, worked for firms of similar size operating in the same 3-digit sector. The identifying assumption is that the remaining variation within 3-digit sector and firm-size cells is uncorrelated with the energy expenditure shares of consumers.

While the SIEED data does not contain information to directly test this assumption, there are reasons to believe that potential violations of it are likely to be of limited quantitative relevance. For instance, von Graevenitz and Rottner (2023) estimate that the share of energy in the total production

Figure 3: The Effect of Energy Cost Shocks on Earnings; for varying time-horizons



Note: The Figure displays point estimates and 95% confidence intervals for τ in specification 1, for varying time-horizons $s \in \{1,2,3,4,5\}$. Each specification includes individual and county fixed effects, as well as year-by-sector by within-sector firm-size tercile fixed effects. Firm size is measured by the number of employees in the firm individual i worked for in year $t-s$. The specifications additionally allow yearly fixed effects to vary over: quintiles of the county-sector-level distribution of employment concentration (Herfindahl-Hirschmann-Index), quintiles of the energy intensity of local production, measured as the share of establishments in each county that are operating in energy-intense sectors (i.e., agriculture, utilities, transportation, manufacturing), and the lagged county-level unemployment rate, respectively. Standard errors are clustered at the county level.

costs of German manufacturing firms is low, averaging around 2-3% for the period 2003 to 2017. Most of it is driven by electricity and gas purchases. Re-assuringly, Table A2 in the Appendix demonstrates that excluding gas or electricity from the energy cost shock measure does not affect the overall pass-through estimates. Petrick, Rehdanz and Wagner (2011) further provide estimates for the set of 3-digit sectors with the highest within-sector variation in energy intensity – which is the relevant metric if one is concerned about a correlation with spatial differences in consumers' energy expenditures.[15] In Appendix Table A4, I show that excluding the counties with the highest and lowest share of employment in these sectors does not affect the estimated pass-through.

Dynamic Adjustments: Considering cumulative exposure over longer-time horizons. While there is no evidence for pre-trends as estimated by the included leads of the energy inflation measure, it is natural to assume that labor market adjustments happen dynamically and not necessarily on a short-term basis – e.g., because of mobility frictions or a lower frequency of wage adjustments. To understand the pass-through of energy prices to earnings on a longer-term horizon,

[15]The list of sectors is (i) mining, (ii) glass, (iii) coke, petroleum products, and nuclear fuel, (iv) locomotives and rolling stock, (v) non-metal recycling, (vi) basic and agro-chemicals, (vii) metal recycling, (viii) basic iron and steel, tubes, (ix) veneer sheets, plywood, laminboard, and the like, and (x) builders' carpentry and joinery.

Figure 3 displays the point estimates obtained by repeating the analysis for cumulative changes over periods of one to five years. Considering longer time horizons reveals an increasing pass-through over time such that over five years, earnings increases fully recover county-specific cost shocks for the average employee. The increasing pattern in Figure 3 suggests a role for frictions to immediate adjustments and/or delayed behavioral responses to cost shocks. To get a better sense of what is driving the positive response of nominal earnings, the next section takes a closer look at different channels of labor market adjustment.

4.2 Adjustment Channels: Why Do Earnings Increase?

From a theoretical point of view, there are several ways to model individual labor supply responses to changes in price levels. People might be encouraged to work longer hours, increase their effort on the job, bargain for higher wages, or search for a new job. In this Section, I am assessing evidence on the relevance of different channels in explaining the documented positive pass-through results.

Adjustments on the Job-to-Job Mobility Margin. A series of recent studies suggest that switching employers might be one channel through which employees are able to recover real earnings losses after price changes (Afrouzi et al., 2024; Bostanci, Koru and Villalvazo, 2022; Bloesch, Lee and Weber, 2024; Pilossoph and Ryngaert, 2023). In line with this idea, column (1) of Table 6 presents estimates of the effect of energy cost shocks on the probability of employer-to-employer (E-E) transitions.

An increase in county-specific energy costs by 1% relative to the previous year increases the probability of switching employers over that period by around 0.3 percentage points. Given the comparatively low labor mobility in Germany, this elasticity of job mobility is non-negligible. Note that the average E-E transition in the estimation sample is accompanied by an increase in earnings of around 6%, whereas increases for people remaining with their current employer are 2.4%. Based on these estimates, job switches more than compensate for the increases in costs. Column (2) of Table 6 further illustrates that job switchers in high-exposure counties are positively selected. Conditional on switching jobs, their earnings gains are even higher than in low-expenditure counties, corresponding to 84% of energy costs on a year-to-year basis. Note that the comparison in column (2) is between two individuals who switch their jobs between years $t - s$ and t but differ in their exposure to energy price increases. This implies that energy cost shocks not only encourage employees to switch jobs, which, on average, entails a significant increase in earnings, but they also

Table 6: The Effect of Energy Cost Shocks on Job-to-Job Mobility

	Pr(E-to-E)	$\Delta ln(earnings)$	
	(1)	(2)	(3)
Yearly Energy Cost Shock	0.297***	0.840***	0.268***
	(0.120)	(0.218)	(0.035)
Sample	Full	Switchers	Stayers
N Individual	869,752	386,020	805,334
N Total	9,923,313	1,373,675	8,257,784

Notes: The Table displays estimates for τ in specification 1, proxying individual energy-price inflation with county-level averages as estimated in Section 3.2: $C^s_{ct} = \sum_g S^g_{c,t-s} \frac{P^g_t}{P^g_{t-s}}$. Column (1) uses an indicator that is equal to 1 in case individual i switched their employer between $t-s$ and t as the outcome variable. Columns (2) and (3) use changes in log earnings as outcomes and restrict the estimation to the sample of job switchers and stayers, respectively. Each specification includes individual and county fixed effects, as well as year-by-sector by within-sector firm-size tercile fixed effects. Firm size is measured by the number of employees in the firm individual i worked for in year $t-1$. Standard errors are clustered at the county level.

make the job switch more aligned with earnings gains.

A second key takeaway from Table 6 is that a positive pass-through of energy prices into earnings is not constrained to the subsample of job switchers alone. Also those employees who stay in their current jobs experience a positive earnings response after increases in energy costs, albeit to a smaller degree (column 3). In fact, using the results in Table 6 for a naive back-of-the-envelope decomposition of average earnings responses implies that around 65% of nominal earnings adjustments stems from people remaining with their current employer. In line with this, when considering a longer time period of five years, a larger share of employees switch jobs irrespective of energy price shocks but the estimated pass-through into earnings increases to around 1 to 1.[16] While a change of jobs appears to be an important response to higher costs in the short run, the results also suggest that local labor markets adjust sufficiently to stabilize employment relationships in the medium to longer term. This could, for instance, imply that once an employee switches their job after a price shock, they are less likely to switch again in the subsequent years. Another explanation is that employers respond to the increasing rate of separations by offering higher compensation to their remaining workers, which decreases their risk of leaving in future periods. The latter mechanism would also help to explain the positive earnings response in the sample of stayers.

[16] The five-year equivalent point estimate to column (1) in Table 6 is 0.46 with a standard error of 0.23. In terms of standard deviations, this implies that a one-standard-deviation increase in energy costs leads to a 0.6 percentage points higher probability of job-to-job transitions, against an average probability of 42%.

Irrespective of one's preferred interpretation of why the effect of energy cost shocks on job transitions decreases in the long run, Table 6 highlights that on a year-to-year basis selected E-E transitions are an important buffer against energy cost shocks. This is not trivial given that cost shocks make transitions more "local". A one standard deviation increase in energy costs reduces the probability that employees commute out of their county of residence to work by 0.5%. Previous research by Agrawal, Jahn and Janeba (2024) demonstrates that when job seekers' geographic job search radius increases (in their case, in response to more generous commuting subsidies), wages do increase as well. The fact that I find both a reduction in commuting and an increase in earnings underlines that average job switches are different for harder-hit individuals.[17]

In Section 5 below, I provide a simple theoretical framework to think about this result. In the model, workers care not only about earnings but also about other firm amenities. In such a setting, workers with higher exposure to price shocks align their choice of employer more with earnings considerations and place less weight on amenities. This makes their transitions positively selected in terms of earnings gains. A remaining question is how this positive selection materializes. Is it because employees with higher cost shocks explicitly target more productive, high-paying firms? Or because, upon transitioning, they bargain more aggressively?

To get a better understanding of the characteristics of firms that job switchers join, Table 7 uses the subsample of employees who changed their jobs between year $t-1$ and t to estimate models similar to specification (1), treating characteristics of the newly joined firms as the outcome variables. Column (1) of the upper panel first calculates the difference in log earnings between the average employee in individual i's current firm and the average employee in their previous firm, using information from year $t-1$. This way, the resulting log difference gives an estimate of the change in earnings each individual can expect simply by joining their new firm, irrespective of bargaining efforts.

The results indicate that job switchers in higher exposure counties are more likely to sort into firms with overall higher earnings potential. The estimated differences correspond to approximately 40% of the overall pass-through among switchers. Job switchers in high-exposure counties also display a higher willingness to join firms in different sectors and to accept jobs in different occupations. If part of the increase in earnings is attributable to sectoral and occupational

[17] The finding that commuting distances decrease in response to higher energy costs is in line with Ready, Roussanov and Zurowska (2019) who study commuting patterns after increases in oil prices for a sample of employees in Minnesota. Besides its implications for labor market dynamics, this finding also suggests that employees respond along the consumption margin. Reducing commuting plausibly decreases expenditures on gasoline, providing an additional buffer against the rising costs of living.

Table 7: Energy Cost Shocks and the Characteristics of Switcher's New Firms

	Expected Change in:	Pr(Switch to Different:)		
	$ln(earnings)$	Sector	Occupation	Task
Energy Cost Shock	0.343^{*}	0.573^{***}	0.487^{***}	0.089
	(0.181)	(0.182)	(0.169)	(0.135)
N Individuals	321,614	386,876	386,876	386,876
N Total	1,075,641	1,378,602	1,378,602	1,378,602

Notes: The Table displays estimates for τ in specification 1, proxying individual energy-price inflation with county-level averages as estimated in Section 3.2: $\sum_g S^g_{c,t-1}\frac{P^g_t}{P^g_{t-1}}$. Each specification includes individual and county fixed effects, as well as year-by-sector by within-sector firm-size tercile fixed effects. Firm size is measured by the number of employees in the firm individual i worked for in year $t-1$. Expected change in $ln(earnings)$ is defined as the difference in log earnings between individual i's current employer and their employer in $t-1$, measured in the year $t-1$. The probability of switching to a different task is equal to 1 if the current job task of individual i is more complex than the performed task in $t-1$. Job complexity is measured at the occupational level and can take four values: unskilled/semiskilled, skilled, complex task, and highly complex task. The probability of switching to a different sector or occupation is based on 3-digit classifications. Standard errors are clustered at the county level.

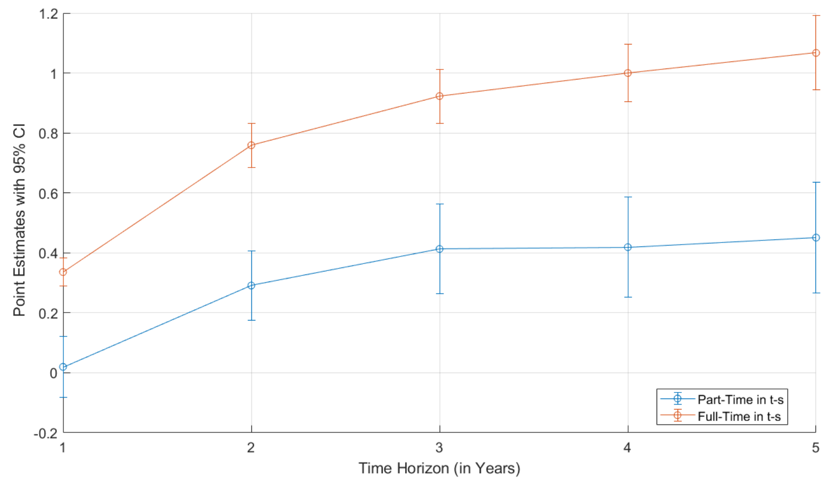
flexibility, then the fact that we see less of it in counties with lower cost increases implies that from the point of view of workers, such shifts are costly. I revisit this point below through the lens of my model when considering broader welfare implications.

The last column of Table 7 finally demonstrates that while workers switch occupations and sectors, their earnings increases are unlikely to be explained by a transition to more complex jobs. The SIEED data provides a measurement of task requirements on the job based on information on job tasks associated with different occupations. Employees in high-exposure counties are not more likely to change to a job with a higher skill requirement than in their previous employment spell.

Adjustments in the Intensive Margin of Labor Supply. The outcome variable underlying the documented nominal earnings response is total daily earnings and not earnings per hour worked. Besides E-E transitions, an alternative margin of adjustment is consequently an increase in working hours. As long as the earnings effect is sufficiently strong, any classic model of labor supply, in which workers choose their hours by trading off the utility of consumption and leisure, would predict an increase in total earnings when energy prices go up. Such intensive margin responses could help explain why earnings increase also for worker staying in their current jobs.

Unfortunately, the SIEED data does not contain detailed measurements of working hours that go beyond an indicator for part-time status. To nonetheless provide some evidence on the

Figure 4: The Effect of Energy Cost Shocks on Earnings; by part-time status



Note: Notes: The Figure displays point estimates and 95% confidence intervals for τ in specification 1, for varying time-horizons $s \in \{1,2,3,4,5\}$. The estimation is based on the subsample of individuals who in $t-1$ were in part- or full-time employment, respectively. Each specification includes individual and county fixed effects, as well as year-by-sector by within-sector firm-size tercile fixed effects. Firm size is measured by the number of employees in the firm individual i worked for in year $t-s$. Standard errors are clustered at the county level.

role of hours-adjustments, Figure 4 uses the part-time indicator to display estimates of the pass-through of energy price changes into nominal earnings, separate for full-time and part-time workers. Interestingly, the pass-through is considerably larger in the sample of full-time workers. Since the variation in hours worked among full-time workers is relatively limited in Germany, we should expect the effects of increases in working hours on earnings to be mostly prevalent in the part-time sample. For them, however, the estimates are statistically indistinguishable from zero for a time horizon of up to three years. Note that the definition of who a part-time worker is is based on the working status in period $t-s$. The subsample thus includes employees who could have transitioned from part-time to full-time in response to the increasing costs, which is one channel of relatively large adjustments in working hours. Even though the presented evidence does not rule out adjustments in hours worked as an explanation of earnings changes, the lack of response among part-time employees places a limit on its quantitative relevance.

Adjustments in the Extensive Margin. So far, the empirical analysis has neglected changes in the extensive margin of employment. One way to rationalize a positive response of nominal earnings to increases in energy prices is a contemporaneous decline in labor force participation and a resulting increase in the marginal productivity of labor.

To investigate this channel, I focus on changes in aggregate employment using firm-level

BHP data for the same period and estimate an empirical specification that, in line with the analysis of employer-employee data before, regresses changes in log employment at firm j in county c and year t, relative to year $t-1$, on the county-specific energy CPI, firm fixed effects and year by sector by sector-specific employment terciles fixed effects. Since results using log-employment as an outcome are highly sensitive to changes in the employment of small firms with one or two employees, I use the lagged number of employees as regression weights. An additional model instead collapses employment at the county-year level and considers variation at this higher level of aggregation. Table 8 contains the results. As before, standard errors are clustered at the county level.

Table 8: Effect on Firm-Level Employment

	$\Delta ln(\#employees)$	
	(1)	(2)
Energy Cost Shock	0.163	0.216**
	(0.169)	(0.102)
N Firms/Counties	1,892,605	400
N Total	16,978,514	8,000

Notes: Energy cost shocks are defined as county-leve energy-specific CPIs, as estimated in Section 3.2: $\sum_g S^g_{c,t-1} \frac{P^g_t}{P^g_{t-1}}$ The outcome in column (1) is the change in log-employment relative to the previous year. The regression adjusts for firm fixed effects and year by sector by within-sector terciles of the firm size distribution fixed effects. Observations are weighted according to firm j's number of employees in period $t-1$. The outcome in column (2) is the change in log employment in county c relative to $t-1$. The regression adjusts for county fixed effects and year by quintiles of *Energy Intensity* fixed effects, where energy-intensity is defined as the share of establishments operating in energy-intense sectors (i.e., agriculture, utilities, transportation, manufacturing). Standard errors are clustered at the county level.

Conditional on adjusting for sector-year-specific shocks, employment responds weakly positively to increases in energy costs. This is contrary to what would be needed to rationalize an increase in earnings based on increases in the marginal productivity of labor. Moreover, the combination of relatively higher employment and higher earnings in response to cost shocks is suggestive of the presence of frictions or rents in the labor market, particularly given the above-demonstrated limited role of adjustments in working hours.

4.3 Heterogeneity in the Pass-Through of Prices into Earnings

The presented empirical evidence demonstrates that nominal earnings respond positively to changes in county- and energy-specific CPIs. This allows consumers to recover a non-negligible share of their idiosyncratic real consumption losses already in the short term, particularly if the cost

Table 9: The Effect of Cost Shocks on Earnings and E-E, by Age

Outcome	Early (age 25-40)	Mid (41-55)	Late (56-65)
$\Delta ln(earnings)$	0.665***	0.190***	-0.030
	(0.119)	(0.041)	(0.126)
$Pr(E-E)$	0.398**	0.117	0.009
	(0.141)	(0.123)	(0.213)
N Individuals	568,565	521,052	205,405

Notes: The Table displays estimates for τ in specification 1, estimated separately by subsample on the outcomes displayed in column 1. Each specification includes individual and county fixed effects, as well as year-by-sector by within-sector firm-size tercile fixed effects. Standard errors are clustered at the county level and displayed in parentheses. Square brackets contain the number of unique individuals included in each subgroup.

shocks encourage job-to-job mobility. Before moving to a theoretical discussion of the implications of these findings, this section explores whether specific subgroups are particularly able to profit from adjustments in their labor supply behavior. A caveat to bear in mind is that, for identification purposes, the proxy for individual exposure to energy price shocks used in this paper is based on county-level CPIs. It is, therefore, not straightforward to cleanly separate treatment effect heterogeneity from non-homogeneity of the cost shock for different subgroups. While the following discussion should be interpreted with caution, it does reveal some noteworthy patterns.

For example, the pass-through of cost shocks into earnings decreases with age (Table A5). Employees between the ages of 25 and 40 are able to recover 67% of county-specific cost increases within a year, which is almost twice the sample average. They are also considerably more likely to increase their job-to-job transitions when costs increase. The higher overall mobility of younger workers is not surprising as one would intuitively expect that their mobility costs are lower – e.g., because of lower investments in firm-specific human capital or a lower likelihood of having kids and a stable relationship.

For younger workers, there appears to be an obvious mapping from higher E-E transitions to higher adjustments in nominal earnings relative to older peers. Table 10, however, shows that this relationship is unlikely to be uniform across the population. Women's responsiveness of job mobility to cost shocks far exceeds that of men, yet the gender difference in terms of pass-through into nominal earnings is considerably smaller and statistically not significant. Conversely, the responsiveness of job mobility to cost shocks is similar for native Germans and foreign workers, but foreign workers experience essentially no increase in nominal earnings after energy price shocks.

The evidence on average E-E responses presented in Section 4.2 highlights that energy cost

Table 10: The Effect of Cost Shocks on Earnings, by Gender, Nationality, and Residence

	Gender		Nationality	
	Male	Female	Non-German	German
$\Delta ln(earnings), yearly$	0.381***	0.481***	-0.057	0.447***
	(0.052)	(0.078)	(0.133)	(0.060)
$Pr(E-E), yearly$	0.105	0.540***	0.280	0.275**
	(0.120)	(0.138)	(0.225)	(0.116)
N Individuals	501,714	367,712	87,584	802,457

Notes: The Table displays estimates for τ in specification 1, estimated separately by subsample on the outcomes displayed in column 1. Each specification includes individual and county fixed effects, as well as year-by-sector by within-sector firm-size tercile fixed effects. Standard errors are clustered at the county level and displayed in parentheses. Square brackets contain the number of unique individuals included in each subgroup.

shocks both encourage job mobility and, conditional on switching, increase the returns to doing so. The discrepancies between who responds with E-E transition and who experiences higher increases in nominal earnings, on the other hand, suggest that there is substantial heterogeneity in the quality of transitions also within counties. There are several potential reasons why this might be the case. Recent work by Caldwell, Haegele and Heining (2024), for instance, demonstrates that individual-level bargaining is a common occurrence in the German labor market and that women are systematically less likely to engage in bargaining and, even when doing so, to bargain aggressively. This more broadly ties into a series of previous studies suggesting that women have a higher relative evaluation of non-wage job components such as short commuting distances (Le Barbanchon, Rathelot and Roulet, 2021), workplace safety (Lavetti and Schmutte, 2023), work flexibility (Mas and Pallais, 2017), and job stability (Wiswall and Zafar, 2018). Morchio and Moser (2024) demonstrates that such amenity differences matter for the gender pay gap, and Card, Cardoso and Kline (2016) find a lower pass-through of firm productivity shocks to women.

Besides a difference in bargaining styles, outside options in the local labor market and skill transferability are arguably highly relevant as well. In recent work, Kline (2025) highlights the central role of the distribution of workers' outside options for determining firms' labor market power and, in turn, the pass-through of shocks into earnings. On average, people in higher-exposure counties increase the probability of changing occupations and sectors. If there are fewer such outside options available or if a person does not have sufficiently general skills to take advantage of such switches, we should naturally expect a lower return to E-E mobility. The lack of skill compatibility or outside options does not necessarily have to objectively describe the state of the market but can reflect subjective worker beliefs (Jäger et al., 2024). The literature on immigration has repeatedly found evidence that immigrants supply labor less elastically (Hirsch and Jahn, 2015), have lower reservation wages (Amior and Stuhler, 2024), and accept lower wages to live in cities with larger migrant networks (Albouy, Cho and Shappo, 2021). Together, this could explain why they are less likely to profit from higher wages after cost-of-living shocks.

5 Theoretical Framework

To organize the empirical analysis, this section discusses a theoretical framework that links exogenous movements in energy prices to individuals' labor market outcomes. I consider a simple model to derive insights into a potential mechanism through which labor market adjustments can counteract the distributional burden imposed by price shocks on heterogeneous consumers. Despite its simplicity, it provides a key intuition: ceteris paribus, cost-of-living shocks decrease individuals' real consumption and thereby increase their marginal utility of income. This makes their labor decisions more elastic, which wage-setting firms internalize. They react by increasing their posted wages. I outline potential extensions and complications at the end of the section.

5.1 The Model

Consider a set of local labor markets $l = 1, 2, ..., L$, each inhabited by a unit mass of workers and a finite number of firms $jl \in J_l$. Workers' and firms' locations are fixed, and workers cannot work for firms outside their local labor market. They consume energy e, exogenously supplied at price q, and a consumption good c, produced by the firms in each labor market and traded across all markets. The model is static: firms post wages, workers observe them and sort across firms, production happens, and workers choose how much to consume of c and e. To align the model with the empirical exercise and allow for heterogenous consumption baskets, local labor markets are heterogeneous with respect to a minimum subsistence level of energy each worker needs to consume. They are otherwise identical. Since decisions are made within local labor markets, I drop the subscript l below for notational simplicity.

The Worker's Problem.

Before turning to the discrete choice over which firm to work for, consider the consumption problem of a worker at firm j with wage w_j. Let the utility of consumption be of the Stone-Geary type with the county-specific subsistence energy level equal to $\bar{e}$. The indirect utility of consumption when working for firm j at wage w_j then is:

$$\begin{aligned} V(w_j, p, q) &\equiv \max_{c,e}\{\gamma ln(c) + (1-\gamma)ln(e-\bar{e})\} \quad s.t. \quad pc + qe = w_j \\ &= ln(w_j - q\bar{e}) + \underbrace{\gamma ln\left(\frac{\gamma}{p}\right) + (1-\gamma)ln\left(\frac{1-\gamma}{q}\right)}_{\equiv\Lambda(p,q)}. \end{aligned} \tag{4}$$

Expenditures on energy as a share of total expenditures are equal to $(1-\gamma) + \gamma\frac{q\bar{e}}{w_j}$. As intended, counties with a higher $\bar{e}$ have a higher expenditure share on energy and, therefore, suffer more severely from changes in q.

The indirect utility of consumption (4) constitutes part of workers' valuation of working for a given firm, and I assume they have full information about the distribution of offered wages $(w_1, w_2, ..., w_J)$. In line with modern monopsony models such as the ones discussed by Card et al. (2018), Lamadon, Mogstad and Setzler (2022), or Berger, Herkenhoff and Mongey (2022), workers additionally value firms' exogenously endowed amenities.

Their maximization problem is:

$$\max_j\{\beta V(w_j, p, q) + \bar{\xi}_j + \xi_{ij}\}, \tag{5}$$

where $\bar{\xi}_j$ is a common valuation of firm j's amenities across consumers, ξ_{ij} is an individual-specific taste-shock for firm j that is i.i.d. across both individuals and firms and β scales the relative importance of consumption and other firm amenities. Assuming ξ_{ij} follows an extreme value distribution, the probability of choosing firm j is:

$$\begin{aligned} Pr(j) &= \frac{exp(\beta ln(w_j - q\bar{e}) + \Lambda(p,q)) + \bar{\xi}_j)}{\sum_{k\in J} exp(\beta ln(w_k - q\bar{e}) + \Lambda(p,q)) + \bar{\xi}_k)} \\ &= \frac{\theta_j(w_j - q\bar{e})^\beta}{\sum_{k\in J}\theta_k(w_k - q\bar{e})^\beta}, \end{aligned} \tag{6}$$

where the second equality follows from defining $\theta_j = exp(\bar{\xi}_j)$ and canceling out $\Lambda(p,q)$, which is common across firms. The probability of choosing firm j is increasing in its amenities, θ_j, and in $(w_j - q\bar{e})$, which is the disposable income after paying for the subsistence level of energy. Workers trade off amenities and consumption, and β governs the weight placed on consumption.

The Firm's Problem.

For illustrative purposes, consider the simplest possible case: firms produce the common consumption good c using a linear production technology with labor, L_j, as its only input and a firm-specific productivity level z_j: $f(L_j) = z_j L_j$.[18] Given the assumption of a unit mass of workers, the labor supply to firm j is given by the workers' choice probabilities. Firms take the labor supply schedule (6) and price p as given and maximize profits by setting their offered wages. As is standard, I assume that firms cannot observe individuals' idiosyncratic tastes and, therefore, cannot offer separate wages to different workers.

Given this classic monopsony set-up, the offered wage will be a mark-down on the firm's marginal revenue product, a function of the labor supply elasticity, ϵ_j, they face. In particular, re-arranging the first-order-condition of the firm's maximization problem yields:

$$w_j = \frac{\epsilon_j}{1+\epsilon_j} p z_j. \tag{7}$$

Importantly, as in Lamadon, Mogstad and Setzler (2022), I consider the case in which firms are atomistic. That is, a firm's decision to change its offered wage is inconsequential to the value of the market as a whole. Under this assumption, we can use the labor supply schedule (6) to derive the following labor supply elasticity:

$$\epsilon_j(w_j, p, q) = \frac{w_j}{Pr(j)} \frac{\partial Pr(j)}{\partial w_j} = \frac{w_j \beta}{w_j - q\bar{e}} = w_j \beta \frac{\partial V(w_j, p, q)}{\partial w_j}. \tag{8}$$

Equation (8) illustrates that the labor-supply elasticity firms face is larger if workers place a higher value on consumption relative to amenities (β). It is also an increasing function of workers' marginal utility of consumption. Given (7), a higher valuation of amenities or a larger marginal utility of consumption will increase their offered wage. Combining (7) and (8) yields the following expression of wages:

$$w_j = \frac{\beta}{1+\beta} p z_j + \frac{1}{1+\beta} q\bar{e}. \tag{9}$$

[18] The production function purposefully does not include energy as an input. If firms produce with various energy intensities, this implies a differential labor demand response to energy price shocks across firms. The focus of this paper, however, is on labor supply responses based on workers' consumption bundles. To this end, the empirical analysis seeks to adjust for differences in firms' production functions across counties and compares workers in firms that are as similar as possible in the energy intensity of production. The theoretical framework replicates this by keeping the production process fixed across local labor markets. In the absence of spatial heterogeneity in the energy intensity of production, including energy as an input complicates the analysis but does not provide additional insights into the distributional effects across space.

Wages in this set-up are a weighted average of the firm's marginal revenue product and workers' minimum income level needed to subsist. If workers care only about consumption and not about amenities ($\beta \to \infty$), wages are equal to the competitive benchmark of the marginal revenue product. Inserting (9) into (6) gives the following expression for the sorting of workers across firms:

$$Pr(j) = \frac{\theta_j (pz_j - q\bar{e})^\beta}{\sum_{k \in J} \theta_k (pz_k - q\bar{e})^\beta}. \tag{10}$$

5.2 Comparative Statics and Distributional Implications

Consider the average wage in a local labor market, $\bar{w} = \sum_j w_j Pr(j)$, and what would happen if energy prices were to increase exogenously (e.g., because of a supply shock on the global market):

$$\frac{\partial \bar{w}}{\partial q} = \sum_j \left[w_j \frac{\partial Pr(j)}{\partial q} + Pr(j) \frac{\partial w_j}{\partial q} \right].$$

From the expression of the labor supply elasticity (8), we can see that $\frac{\partial \epsilon_j}{\partial q} > 0$ for all j. For a given set of wages, workers lose disposable income in response to an energy price shock. This increases their marginal utility of consumption and, as a consequence, their elasticity of labor supply. Internalizing this response, firms raise wages at the expense of lower profits. This implies that average wages go up as long as workers are not systematically more likely to switch to lower-paying firms after the price shock. It is straightforward to show that this is not the case. Consider the odds ratio $p_{jk} = \frac{Pr(j)}{Pr(k)}$ for any two firms $j \neq k$. Inserting the expression for the labor supply to firm j and k (equation 10), and differentiating with respect to q yields:

$$\frac{\partial p_{jk}}{\partial q} = \bar{e}\beta \Big[\frac{p(z_j - z_k)}{(pz_k - q\bar{e})(pz_j - q\bar{e})} \Big] p_{jk}, \tag{11}$$

which implies that $\frac{\partial p_{jk}}{\partial q} > 0 \iff z_j - z_k > 0$.[19] Higher-paying/more productive firms will attract more workers after an increase in energy prices, increasing the average wage in the local labor market.

This partially shields workers from a decrease in real consumption. The remaining question is whether counties that, through their consumption bundles, have a higher exposure to energy price shocks will see their wages increase more. From expression (9), we can see directly that firms

[19] This reasoning is in partial equilibrium, as it treats p as constant. Since the goal of the theoretical and empirical analysis is a comparison of relative wage responses across labor markets and p is not determined locally, this is innocuous. I discuss the issue further in Appendix A.4 when considering extensions to the baseline model.

will increase wages more strongly in counties with higher energy expenditure shares. We also know that higher-paying firms see their labor force increase in response to energy prices. As long as this reshuffling of the labor force is not less pronounced where energy expenditures are high, the wage response of average wages to energy price shocks will be positively correlated with $\bar{e}$.

To see that this is in fact not the case, differentiate (11) further with respect to $\bar{e}$:

$$\frac{\partial^2 p_{jk}}{\partial q \partial \bar{e}} = \frac{\partial p_{jk}}{\partial q}\Big[\underbrace{\frac{1+p_{jk}}{\bar{e}p_{jk}}}_{>0} + q\frac{p(z_j+z_k)-2q\bar{e}}{(pz_j-q\bar{e})(pz_k-q\bar{e})}\Big].$$

In equilibrium, $pz_j > q\bar{e} \, \forall \, j$, as no worker would choose to work for a firm offering less than $q\bar{e}$ and no profit-maximizing firm will pay more than their marginal revenue product, pz_j. Any firm for which the inequality doesn't hold would consequently be inactive. This implies that the term in square brackets is strictly positive, and thus, the sign of the cross-derivative is the same as the sign of the first derivative. In line with the empirical evidence, the sorting toward higher-paying firms is then even more pronounced in labor markets with high energy expenditures. In lower-cost areas, sorting across firms remains relatively more aligned with a maximization of amenities.

5.3 Discussion

The model predicts that increases in the labor supply elasticity of workers reduce the divergence in real income between high and low-energy expenditure labor markets. This is the result of a re-evaluation of the relative importance of amenities and consumption. While wages increase relatively more in high-exposure markets, this comes at the cost of choosing employers that are less appealing in terms of non-wage amenities. The impact of labor supply adjustments for the distribution of consumption is consequently not identical to its implication on welfare. Recently, Afrouzi et al. (2024) and Guerreiro et al. (2024) highlighted that workers dislike inflation also because it requires them to take actions on the labor market that are costly in utility terms. In my setting, such actions are quantified by the choice of lower-valued amenities.[20] We could, for instance, interpret the empirical evidence on workers' transitions to other occupations and sectors as moves towards firms that are further away from their preferred idiosyncratic choice (i.e., that have a lower value of $\bar{\xi}_j$ and ξ_{ij}). This helps to explain why sectoral and occupational changes happen more frequently when costs are high, and workers are content to stay with lower-paying

[20] Mongey and Waugh (2024) provide a thoughtful discussion on how to think about welfare more broadly in discrete choice settings such as the one outlined here.

firms when costs are low. The model generally provides a rationale for why job transitions are particularly positively selected for earnings gains in high energy-expenditure counties.

The outlined theoretical framework is kept as simple as possible to illustrate one key mechanism. Appendix A.4 discusses several extensions to the model and their implications for the empirical analysis. The extensions include non-atomistic firms, non-linear production functions, a distinction between job switchers and stayers, unemployment as a choice option, allowing workers to switch across local labor markets, and the price changes of other goods, including local and global goods. Importantly, these extensions do not affect the qualitative prediction of the framework outlined above, even if the magnitude of the predicted effects is altered.

6 Concluding Remarks

This paper estimates the pass-through of cost-of-living shocks into earnings and demonstrates that individual labor supply responses significantly reduce the distributional consequences of price changes that one would expect from approximations based on consumers' consumption bundles. Relying on county-level differences in consumption patterns to construct measures for heterogeneous exposure to movements in energy prices, the results indicate that employees can fully recover county-specific cost increases over a five-year horizon through higher nominal earnings. In the short term, it is particularly job-to-job mobility that offers a route to lessen the burden of higher energy costs.

I discuss changes in individuals' labor supply elasticities, resulting from an increase in their marginal utility of income after the cost shock as a potential explanation. In a model with wage-setting firms, such increases in the elasticity of labor supply reduce firms' mark-downs on wages. Interestingly, this mechanism suggests that relief policies aimed at reducing the burden of cost shocks on consumers could unintentionally keep their labor supply responses and, consequently, the allocation of rents between firms and workers constant. The results in this paper, therefore, are relevant both for the measurement of labor market dynamics after price shocks and for the design of policies to address their distributional consequences. Policymakers and researchers interested in doing so should be cautious to neglect the importance of endogenous labor supply responses.

While the focus of this study is on dynamics in the shorter run of one to five years, there is a large literature discussing long-run trends in inequality (e.g., Card, Heining and Kline, 2013, for the case of Germany). Recently more attention has been devoted to the importance of differences in consumption patterns and the measurement of real inequality trends (Diamond and Moretti, 2021; Dustmann, Fitzenberger and Zimmermann, 2022; Moretti, 2013). An interesting open question for future research that emerges from this study is the degree to which we can generalize from the pass-through of shocks moving the price of necessities, such as energy, to that of other prices. Answering this question will provide additional insights into the longer-run dynamics of spatial inequality, as it provides a tighter link between local costs of living and the sorting of firms (Gaubert, 2018) and workers (Card, Rothstein and Yi, 2024) across space.

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Appendix

Labor Market Dynamics and the Distributional Impact of Price Shocks

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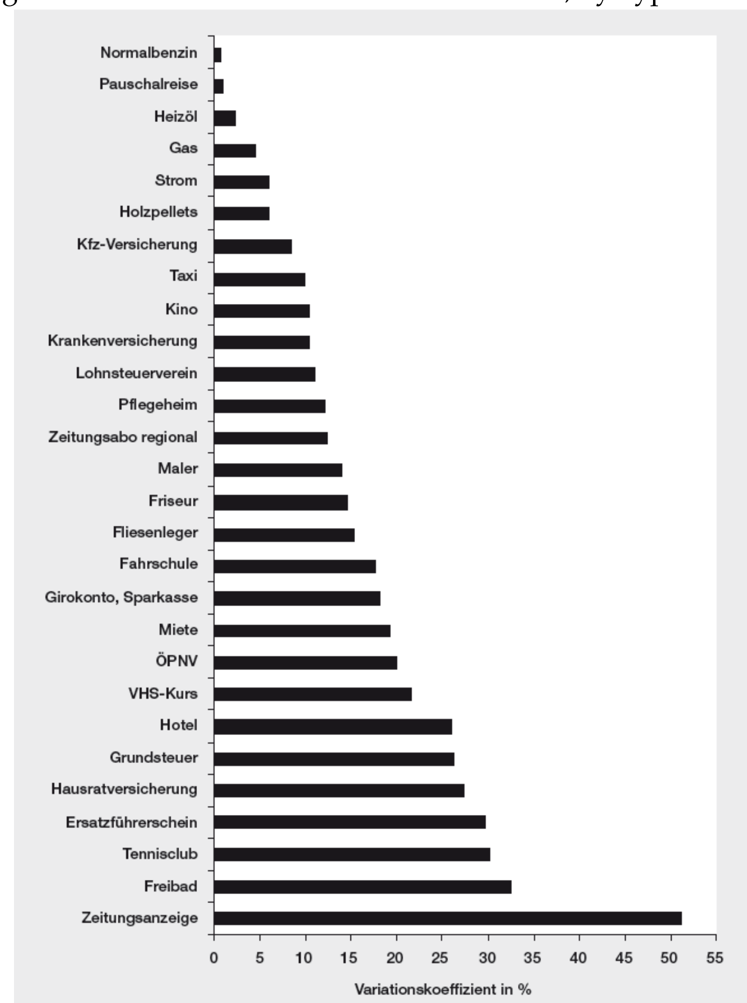
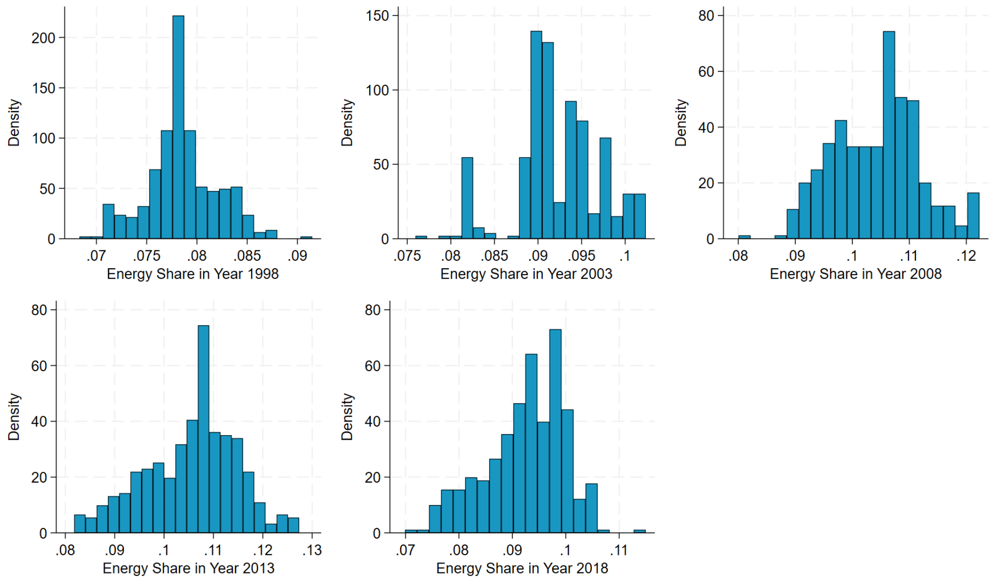
A.1 Additional Figures

Figure A1: Variation in Prices across Counties, by Type of Good



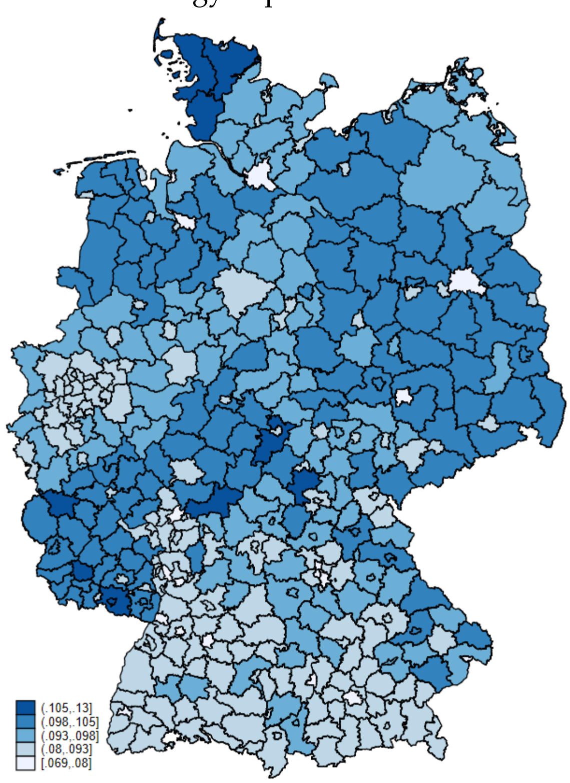
Note: The figure is taken from BBSR (2009) and displays coefficients of variation for prices of various goods across German counties in 2008. The translation of each good type from German to English is (in decreasing order): Gasoline, package holidays, heating oil, gas, electricity, wood pellets, car insurance, taxi fee, cinema ticket, health insurance, membership fee income tax association, nursing home, subscription to regional newspaper, painter, haircut, tiler, driving instructions, fees for checking account, rent, public transportation, community college course fees, hotel, property tax, household insurance, replacement driving license, membership fee tennis club, outdoor pool, newspaper advertisement.

Figure A2: Distribution of Estimated Energy Expenditure Shares, by EVS Wave



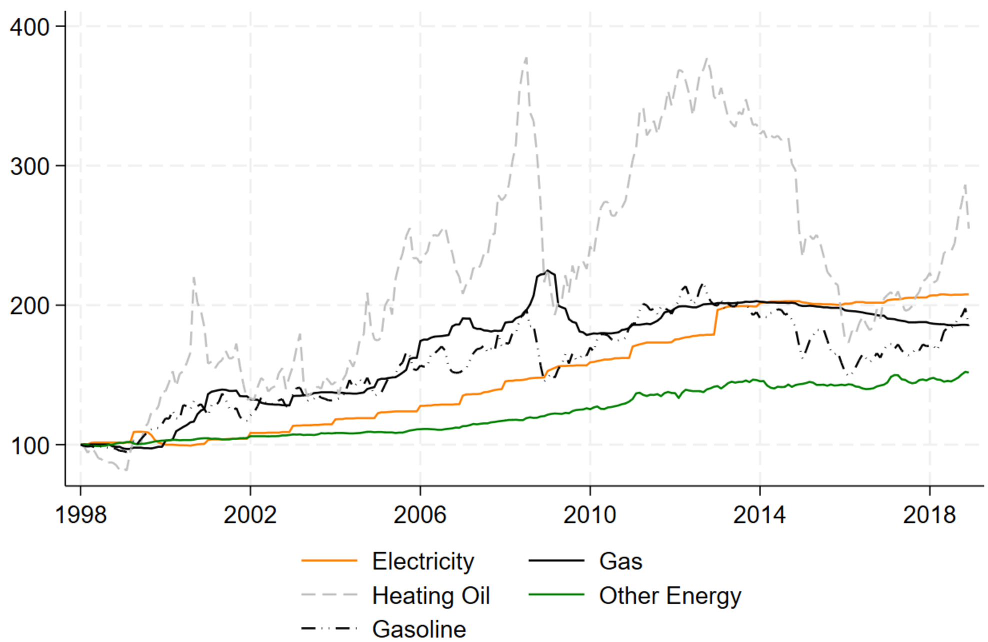
Note: The Figure shows the distribution of estimated county-level averages for total expenditure shares of energy goods, including gasoline, gas, oil, electricity, and other types of energy. Source: Einkommens- und Verbrauchsstudie 1998, 2003, 2008, 2013 and 2018 each Basic File 3, own calculations.

Figure A3: Estimated Energy Expenditure Shares in EVS Wave 2018



Note: The figure presents county-level estimates of energy expenditure shares, following the approach discussed in Section 3.2. Source: Einkommens- und Verbrauchsstudie 2018 Basic File 3, own calculations.

Figure A4: Monthly Consumer Price Series for Energy Goods



Note: The figure plots a series of average monthly prices, normalized to 100 in January 1998. Sources: DESTATIS.

A.2 Additional Tables

Table A1: Summary Statistics – BHP Data

	Mean	*S.D.*	*N*
Average Daily Earnings	72.31	42.25	17,221,351
Pct. 25 Daily Earnings	64.33	35.64	17,221,351
Pct. 75 Daily Earnings	78.51	48.90	17,221,351
Number of Employees	16.17	113.37	20,684,608
Average Employee Age	41.63	8.17	20,684,608
Year-to-Year Change in log employment	0.02	0.37	17,923,543
Five-Year Change in log employment	0.06	0.58	10,715,722
Share of Employees that are:			
Female	0.55		20,684,608
German Citizen	0.92		20,684,608
Part-time employee	0.22		20,684,608

Notes: The table displays summary statistics for the BHP data, excluding firms without any social security employees and with a workforce that, on average, is below 25 or above 65 years old. *Abitur* corresponds to the university-qualifying high school diploma in Germany.

Table A2: Year-to-Year Energy Cost Shocks on Earnings; by Type

		Exclude Energy Type:					
		None	Gasoline	Gas	Oil	Electricity	Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\sum_g S^g_{c,t-1} \frac{P^g_t}{P^g_{t-1}}$		0.427***	0.505***	0.452***	0.489***	0.484***	0.357***
		(0.057)	(0.074)	(0.069)	(0.069)	(0.060)	(0.059)
$S^{gasoline}_{c,t-1} \frac{P^{gasoline}_t}{P^{gasoline}_{t-1}}$	0.563***						
	(0.094)						
$S^{gas}_{c,t-1} \frac{P^{gas}_t}{P^{gas}_{t-1}}$	0.523***						
	(0.124)						
$S^{oil}_{c,t-1} \frac{P^{oil}_t}{P^{oil}_{t-1}}$	0.240***						
	(0.092)						
$S^{electricity}_{c,t-1} \frac{P^{electricity}_t}{P^{electricity}_{t-1}}$	0.133						
	(0.211)						
$S^{other}_{c,t-1} \frac{P^{other}_t}{P^{other}_{t-1}}$	0.468**						
	(0.191)						
N Individuals	869,437	869,437	869,437	869,437	869,437	869,437	869,437
N Total	9,890,000	9,890,000	9,890,000	9,890,000	9,890,000	9,890,000	9,890,000

Notes: The Table displays estimates for τ in specification 1, proxying individual energy-price inflation with county-level averages as estimated in Section 3.2. All specifications include individual and county fixed effects, as well as year-by-sector by within-sector firm-size tercile fixed effects. Each model additionally allows yearly fixed effects to vary over: quintiles of the county-sector-level distribution of employment concentration (Herfindahl-Hirschmann-Index), quintiles of the energy intensity of local production, measured as the share of establishments in each county that are operating in energy-intense sectors (i.e., agriculture, utilities, transportation, manufacturing), as well as across differences in the lagged county-level unemployment rate. Standard errors are clustered at the county level.

Table A3: The Effect of Year-to-Year Energy Cost Shocks on Earnings in LLMs

	Outcome = $ln(Earnings_{it}/Earnings_{i,t-1})$				
	(1)	(2)	(3)	(4)	(5)
Yearly Energy Cost Shock	0.506***	0.483***	0.493***	0.419***	0.439***
	(0.080)	(0.065)	(0.060)	(0.099)	(0.059)
N Individuals	869,437	869,392	869,379	869,437	868,799
N Total	9,890,000	9,887,660	9,887,333	9,890,000	9,860,806
Match HHI		✓			✓
Match Energy-Intensity			✓		✓
Match Unemployment				✓	✓

Notes: The Table is identical to Table 4, replacing all shocks and variables measured at the county-level with respective measurements at the commuting-zone level. The crosswalk from counties to commuting zones is based on the definition by BBSR. There are 223 unique commuting zones and standard errors are clustered at that level.

Table A4: Pass-Through When Dropping Counties with High (Low) Share of Employment in Sectors with High Variance in Energy-Intensity

	Outcome = $ln(Earnings_{it}/Earnings_{i,t-1})$			
	(1)	(2)	(3)	(4)
Energy Cost Shock	0.427***	0.404***	0.388***	0.389***
	(0.057)	(0.061)	(0.064)	(0.053)
N Individuals	869,437	788,927	718,111	733,690
N Total	9,890,000	8,845,885	7,952,953	8,145,090
Sample	Full	Drop Top 10%	Drop Top 20%	Drop Bottom & Top 10%

Notes: The Table displays estimates for τ in specification 1, proxying individual energy-price inflation with county-level averages as estimated in Section 3.2: $C^1_{ct} = \sum_g S^g_{c,t-1} \frac{P^g_t}{P^g_{t-1}}$. Each specification includes individual and county fixed effects, as well as year-by-sector by within-sector firm-size tercile fixed effects. Firm size is measured by the number of employees in the firm individual i worked for in year $t-1$. Columns (2), (3), and (4) drop all individuals residing in counties for which the employment share in sectors with a known high variance of energy intensity is among the top 10%, top 20%, and Bottom or Top 10% of the cross-county distribution, respectively. The mean employment shares of high energy-intensity variance industries per decile (40 counties) of the cross-county distribution are: 0.25%, 0.6%, 1.0%, 1.4%, 1.8%, 2.4%, 3.2%, 4.2%, 6.6%, and 15.0%. The 3-digit sectors with the highest within-sector variance in energy-intensity according to Petrick, Rehdanz and Wagner (2011) are: (i) mining, (ii) glass, (iii) coke, petroleum products, and nuclear fuel, (iv) locomotives and rolling stock, (v) non-metal recycling, (vi) basic and agro-chemicals, (vii) metal recycling, (viii) basic iron and steel, tubes, (ix) veneer sheets, plywood, laminboard, and the like, and (x) builders' carpentry and joinery. Energy intensity is defined as the kWh of energy input per €1,000 of output. The measure of variation in energy intensity is (p90-p10)/p50. Standard errors are clustered at the county level.

Table A5: The Effect of Cost Shocks on Earnings and E-E, by Educational Attainment

Outcome	Below Abitur	Abitur	Academic
$\Delta ln(earnings)$	0.295***	0.291***	0.718***
	(0.044)	(0.109)	(0.103)
$Pr(E-E)$	0.252**	0.022	0.446***
	(0.116)	(0.184)	(0.157)
N Individuals	610,746	124,986	166,422

Notes: The Table displays estimates for τ in specification 1, estimated separately by subsample on the outcomes displayed in column 1. *Abitur* is the degree obtained when finishing the university-qualifying high-school track of the German school system. Each specification includes individual and county fixed effects, as well as year-by-sector by within-sector firm-size tercile fixed effects. Standard errors are clustered at the county level and displayed in parentheses.

A.3 Imputation of County-Level Expenditure Shares

Both data sets provided by IAB-FDZ, the Sample of Integrated Employer-Employee Data and the Establishment History Panel, contain geographic information on firms' and individuals' locations at the level of the 400 administrative counties in Germany. The Income- and Expenditure Survey (EVS) data set, on the other hand, provides information on Germany's 16 regions as the smallest level of geographical aggregation. Using household's county of residence it does, however, further distinguish between households living in areas corresponding to one of three agglomeration types depending on the population density and share of the local population that lives in cities: urban areas ($>$ 50% lives in cities and population density is above $150/km^2$), semi-urban ($>$ 50% lives in cities, population density is below $150/km^2$ or $<$ 50% lives in cities but population density is above $100/km^2$), and rural areas ($<$ 50% lives in cities and population density is below $100/km^2$).

To harmonize the geographic units in all data sets and to predict county-level energy expenditure shares as suggested in Section 3.2, I first use region-by-agglomeration type locations, c, to estimate regressions of the type

$$S^g_{h,c} = \pi_c + X_{h,c}\beta + u_c, \tag{12}$$

where $S^g_{h,c}$ is household h's expenditure share on energy good g, π_c are location c fixed effects and $X_{h,c}$ is a set of covariates.

There is a direct mapping between each German administrative county and c, which allows me to predict stylized county-level expenditure shares. To further distinguish between counties within a region-by-agglomeration type cell, I use information on county-level characteristics provided by the Federal Institute for Research on Building, Urban Affairs, and Spatial Development (BBSR) and extract information on each county's infrastructural features that likely predict energy expenditures from the INKAR database (https://www.inkar.de/): average living space per household member and the share of buildings that consist of at least three apartments as proxies for the available housing stock, and the average number of cars per inhabitant as a proxy for commuting patterns. Each variable has an empirical counterpart in the EVS data that is included as a covariate in $X_{h,c}$. After estimating the parameters of specification (12), I predict county-level expenditure shares using $\hat{\pi}_c$ and the estimated coefficients on each of the three outlined variables. All other socio-demographic information is kept at the sample mean to adjust for household sorting as discussed in Section 3.2.

A.4 Extensions of the Baseline Theoretical Framework

Work in Progress.